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An Analysis of the Challenges of Implementing M-MIMO in 5G With a CS Approach

Mohammad Ali Abedi
Lecturer at Imam Hossein University for Gaurds Training and Officers
m.aliabedi@ut.ac.ir

Abstract
Due to the limited scattering of local scatterers on the BS side in fifth-generation massive multiple-input multiple-output systems, the channels tend to be sparse. As a result, it is better to extract the potential sparsity in the channel estimation process and use compressive sensing as a very good working method for estimation efficiency. For this reason, in this paper, after analyzing the structure of massive multiple-input multiple-output systems, we examine the method of compressive sampling and compressive measurement sizes, and follow the methods of retrieval of sparse signals, including BP and LASSO, and then from it, we analyze the challenges of implementing massive multiple-input multiple-output systems and the work done in this field, and at the end, we simulate the proposed channel estimation solution, in which using compressive sensing in these systems and compared with other proposed methods, we realize the superiority of the proposed method.

Keywords: compressive sensing, sparse signal, compressive measurement, sparse recovery.

1- Introduction

Much research has been done on the achievable limitations of multiple-input-multi-output systems, beginning with work such as (Keusgen, 2003)) and predicting that MIMO systems are capable of Provide high link rates telecommunications services as well as their reliability. Today, MIMO systems are at the core of wireless telecommunications standards such as LTE, IEEE 802.16 (WiMAX) and IEEE 802.11n (WiFi-n). Random multi-path fading, once a major barrier to reliable telecommunications, are now used to increase capacity C, quality of service (QoS), and signal-to-noise ratio.

In general, a wireless telecommunication link is identified with three main components: 1- Noise, 2- Multi-path fading, 3- Interference. Today, multi-path noise and fading are not limiting factors for advanced MIMO receivers; instead, interference is significantly limiting. (Sanguino & Roberts, 2011, (Stüber et al., 2004).

Multiple antennas in the transmitter and receiver can be used to increase the rate of information through multiplexing or to provide system reliability through multiplication (Oestges & Clerckx, 2007). In order to increase capacity, independent information sequences are sent to the antennas. This is known as spatial multiplexing. Assuming that the transmitter antennas are well separated and that the medium has a good transmitter, the transmitted signals observe a specific space that allows the receiver to assemble sequences. To separate. Under optimal conditions, the capacity increases by $a\min(N_T,N_R)$ factor that is N_T and N_R the number of transmitting and receiving antennas. In addition, most receivers need to be $N_R \geq N_T$. Of course, the channel estimation algorithms discussed in this dissertation are not limited to this condition.

An alternative to spatial multiplicity that increases a user's throughput is proposed using spatial multiplexing that intends to increase the signal-to-noise ratio. In this case, the same information is sent from all transmitter antennas. It is relatively unlikely that all the links between the transmitter and receiver antennas will receive deep fading at the same time, so the transmission of a signal is very reliable. Spatial multiplexing and spatial multiplicity are two modes of interest for MIMO channels.

In a wireless MIMO system, the throughput of a system is limited using existing interference. It is clear that increasing the SNR by increasing the transmitted power can not reduce the interference effect of other antennas. Therefore, advanced MIMO methods have an improved effect on interference and the possibility of reusing a resource. These methods can be divided into 4 parts, which include rejecting interference, avoiding interference, aligning interference, and using interference. Different strategies can be used for single-user and multi-user systems. An overview of MIMO methods applicable to fourth-generation telecommunications such as LTE-A is presented (Boudreau et al., 2009). One of the techniques that is considered is the use of beam forming. Using the amplitude and phase control of the signal emitted from each of the antennas, it is possible to provide directional transmission in such a way as to create constructive and destructive interferences at the desired angles. The receiver can also adjust its beam to reach the maximum direction to reach the maximum direction (Mietzner et al., 2009). The SNR interest that results from this is called the array interest.

Because compressive sensing is a mathematical method for signal reconstruction from finite samoling, it suggests that sampling rates below the Nyquist rate are sufficient to reconstruct sparse signals. And uses the property of sparsity - being the primary signal. Compressive sensing methods perform better than other methods when working with sparse signals. We will see that using compressive-based methods, sparse channels can be estimated more accurately, and therefore lower bit error rates can be achieved. Due to the sparsityof the channel in mass multi-input multi-output systems, compressive sensing is the best solution.

1-1 Article Structure

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The continuation of the article is as follows: in the second part, we will model narrowband MIMO, then in the third part, we will discuss compact sensor and define thin signal, compact size and methods of thin signal retrieval. In the following, we will analyze the challenges of implementing M-MIMO and the work done in this field, and then we will review the simulation performed, and finally, we will conclude the work of the proposed topics.

2- Narrow Band MIMO Model

For a MIMO system with N_T transmit antenna and N_R receive antenna, the MIMO channel for l^{th} subcarrier of the k^{th} OFDM symbol can be displayed as a $H \in \mathbb{C}^{N_R \times N_T}$ matrix.

$$\mathbf{H}[l,k] = \begin{bmatrix} h_{11}[l,k] & h_{12}[l,k] & \dots & h_{1N_T}[l,k] \\ h_{21}[l,k] & h_{22}[l,k] & \dots & h_{2N_T}[l,k] \\ \vdots & \vdots & \ddots & \vdots \\ h_{N_R1}[l,k] & h_{N_R2}[l,k] & \cdots & h_{N_RN_T}[l,k] \end{bmatrix} \quad (1)$$

In this regard, $h_{nm}[l,k]$ is the gain of the channel between the n and m antennas and the receiver and transmitter in l^{th} subcarrier from k^{th} symbol.
With complete channel information, the capacity of a MIMO system in a subcarrier is:

$$C = E\left\{\log\det\left(I_{N_R} + \frac{\gamma}{N_T}\mathbf{H}[l,k]\mathbf{H}[l,k]^H\right)\right\} \quad (2)$$

Which in this regard γ is the amount of SNR. Assuming that the channel matrix is complete and the total transmitted power is constant, the capacity increases linearlywith $\min(N_T,N_R)$. Linear increase is obtained by increasing the number of antennas only if both the transmitter and receiver increase their antennas simultaneously. If the number of antennas is limited on one side (for example in the receiver), the capacity is limited to N_T and the push to $N_R \log(1+\gamma)$. On the other hand, if the number of transmitter antennas is constant and the receiver antennas increase, the capacity increases with $\log(N_R)$. The main difference between the above two modes is that increasing the number of receiver antennas increases the received power. Of course, since the transmitted power is constant, the available power is distributed among all transmitted antennas. Therefore, the total power does not increase with the number of transmitter antennas. Figure (1) shows the capacity as a function of the number of transmitting and receiving antennas.

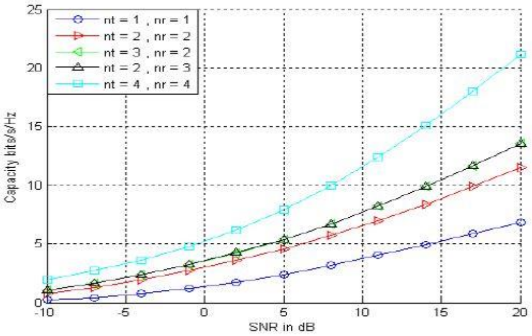

Figure 1. Capacity in a MIMO system as a function of SNR and number of transmitter and receiver antennas (Noor-A-Rahim et al., 2011).

3- Compressive Sensing

We are at the heart of a digital revolution driven by the development and expansion of new measurement systems with increasing quality. The theoretical origins of this revolution are based on the early work of Kettlenikov, Nyquist, Shannon, and Whitaker on the sampling of finite and continuous time signals. (G. Baraniuk et al., 2011). Their results show that the signal, image, or sound can be completely reconstructed from samples of the same distance obtained from the original signal at the Nyquist rate. By applying this principle, many processing systems have been transformed from analog to digital. The digitalization of systems leads to the production of measurement and processing systems that are cheaper and more flexible. As a result of this success, the amount of information generated by the measurement systems turned from a drop to a flood. Unfortunately, in many important applications, the Nikequist rate is so high that we come across many examples. On the other hand, it may be impossible and costly to build a tool that can collect such samples at the required rate.
We usually rely on compression to examine the logical and computational challenges we face in dealing with such large-scale information. One of the most popular techniques for signal compression is coding in the conversion domain, which seeks to find a basis that gives us a sparse or compressible representation of the signal. sparsity means a state in which the signal in length can be displayed with a non-zero coefficient, and compressible signal means a state in which the signal can be approximated only in a non-zero coefficient. Both sparse and compressible signals can be displayed with high quality while maintaining the value and location of the largest signal coefficients. This process is called sparsity approximation.
Compressive sensing uses non-adaptive linear imagery that preserves the structure of the signal. This issue has received a lot of attention in recent years. The main reason for this attention is that in compressive sensing by replacing the sample concept with a new concept called measurement, the original signal can be retrieved with a much smaller number of

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measurements compared to the required number of samples. Measurement is actually a random linear combination of signal samples with which the original signal can be reconstructed. compressive measurement significantly reduces sampling and computational costs for sparse and compressible signals. The Nyquist-Shannon sampling theorem states the minimum number of samples to detect a limited band signal; But if the signal is sparse, we can significantly reduce the number of sizes that need to be stored. As a result, we may be able to get better results than traditional results when measuring a sparse signal. compressive Sampling Instead of sampling at a high rate and then compressing the sampled data, there are ways to compress the data and then measure the data at a lower sampling rate.

3-1 Sparse signal

A signal $\mathbf{x} \in \mathcal{R}^N$ is a signal with a sparsity $S \ll N$ on the space consisting of $\boldsymbol{\psi}_1$ to $\boldsymbol{\psi}_N$ vectors, that is, the space $\boldsymbol{\Psi} = [\boldsymbol{\psi}_1, \boldsymbol{\psi}_2, \dots, \boldsymbol{\psi}_N]$ we say, whenever $\mathbf{x}$ it can be expressed by the linear composition of S vector of the $\boldsymbol{\Psi}$. that's mean,

$$\mathbf{x} = \boldsymbol{\Psi\theta} \tag{3}$$

Where $\boldsymbol{\theta}$ is the coefficient vector $N \times 1$ that has only S non-zero elements. Many real signals are not strictly sparse, but can be compressed into a specific space (that is, many non-zero vector elements are very small in that space (Candes & Romberg, 2005). Since only a small number of coefficients outperform the rest of the coefficients, compressible signals can be modeled with a thinner S signal that S contains a larger, non-zero coefficient (E. J. Candès, 2006)

3-1-1 Compressive Measurements

In the compressive sensing, measurements are not obtained by direct sampling of the sparse signal, but by measuring a limited number of linear samples of the signal. Linear sizes can be expressed as:

$$\mathbf{y} = \boldsymbol{\Phi}\mathbf{x} \tag{4}$$

Showed that $\boldsymbol{\Phi}$ it is an imaging matrix $M \times N$ and the number of dimensions M is much less than the N dimensions. Suppose we display the dimensions with $\mathbf{y} = [y_1, y_2, \dots, y_M]^T$ and $\boldsymbol{\Phi} = [\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots, \boldsymbol{\phi}_M]^T$, then each dimension is equivalent to the image of $\mathbf{x}$ on the $\boldsymbol{\phi}_i$ signal, i.e.

$$\mathbf{y}_i = \langle \mathbf{x}, \boldsymbol{\phi}_i \rangle \tag{5}$$

Where $i \in \{1,2,\dots,M\}$. If we achieve the product of internal multiplication in the analog field, then the sampling rate will decrease.
Having dimensions $\mathbf{y}$, the sparse signal $\mathbf{x}$ can be reconstructed using the nonlinear optimization method and knowing that $\mathbf{x}$ is sparse based on $\boldsymbol{\Psi}$. Of course, for a signal to be successfully reconstructed, the matrix $\boldsymbol{\Phi}$ must have properties. Asymmetry matrixes $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ is a key factor for successful reconstruction of $\mathbf{x}$. That is $\boldsymbol{\phi}_i$, it does not have a compressive display on $\boldsymbol{\Psi}$ and $\boldsymbol{\psi}_i$ does not have a compressive display. (G. Baraniuk et al., 2011) using the following equation, a numerical criterion can be used to express the inconsistency of the two.(J. Candès et al., 2006).

$$\mu(\Phi,\Psi) = \sqrt{N} \sup\{|\langle \boldsymbol{\phi}_i, \boldsymbol{\psi}_j \rangle| : \boldsymbol{\phi}_i \in \boldsymbol{\Phi}, \boldsymbol{\psi}_j \in \boldsymbol{\Psi}\} \tag{6}$$

If $\boldsymbol{\phi}_i$and $\boldsymbol{\psi}_j$ have a single energy, then $\mu \in [1,\sqrt{N}]$. It should be noted that if each of the matrix elements is selected from a random distribution and i.i.d, it will most likely $\boldsymbol{\Phi}$ be non-coherence with each base $\boldsymbol{\Psi}$ and $\mu(\boldsymbol{\Phi},\boldsymbol{\Psi})$ closer to one. The conventional distributions used are the Gaussian and Bernoulli distributions.
One way to construct a measurement matrix $\boldsymbol{\Phi}$ that retrieves a signal with sparsity S is to use the finite isometric property (RIP) of a matrix. For any integer $S = 1,2,\dots,N$, the isometric constant δ_s for a matrix $\boldsymbol{\Phi}$ is the smallest number for which the relation

$$(1-\delta_s)\|\mathbf{x}\|_2^2 \le \|\boldsymbol{\Phi}\mathbf{x}\|_2^2 \le (1+\delta_s)\|\mathbf{x}\|_2^2 \tag{7}$$

Hold for all signals sparsely. The matrix $\boldsymbol{\Phi}$ has the property of RIP order S, if δ_S is much smaller than one. Having the RIP property indicates that each subset of the $\boldsymbol{\Phi}$ matrix columns behaves with less cardinality than S an orthonormal system, indicating that x is not in the empty space of the $\boldsymbol{\Phi}$ matrix. If δ_{2S} is small enough, we will have for two signals x_1 and x_2 that are sparse with S:

$$\begin{aligned}(1-\delta_{2s})\|\mathbf{x}_1-\mathbf{x}_2\|_2^2 &\le \|\boldsymbol{\Phi}(\mathbf{x}_1-\mathbf{x}_2)\|_2^2 \\ &\le (1+\delta_{2s})\|\mathbf{x}_1-\mathbf{x}_2\|_2^2\end{aligned} \tag{8}$$

That is, the RIP property maintains the distance between each pair of signals with a sparsity S in the domain of size, which ensures the stable recovery of the signal with sparsity S of compact dimensions. The measurement matrix $\boldsymbol{\Phi}$ can be constructed with i.i.d data with a Gaussian random distribution with zero mean and variance $^1/_M$ or a Bernoulli random distribution with size $^1/_{\sqrt{M}}$. It has been observed that if $M = CK\log N \ll N$ where $C \ge 1$; The $\boldsymbol{\Phi}$matrix follows the RIP property and is suitable for stable signal reconstruction with sparsity S.
The suitability of the stochastic measurement matrix for compact measurement can be investigated with the Johnson & Lindensterus (JL) Lam in the field of dimensional reduction (Johnson & Naor, 2010). If $\boldsymbol{\Phi}$ made from a random distribution and all its rows are normalized, JL is established, then most likely the following relation is established:

$$\begin{aligned}(1-\varepsilon)\|\mathbf{x}_1-\mathbf{x}_2\|_2^2 &\le \|\boldsymbol{\Phi}(\mathbf{x}_1-\mathbf{x}_2)\|_2^2 \\ &\le (1+\varepsilon)\|\mathbf{x}_1-\mathbf{x}_2\|_2^2\end{aligned} \tag{9}$$

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Where ε small enough and the signals are sparse. What is clear from Equation (9) is that the stochastic matrix is a stable encapsulation of sparse signals in the domain of measurements. The property of RIP can be deduced as a direct result of JL leakage (R. Baraniuk et al., 2008).
Another way to obtain compact measurements is random sampling in a conversion domain $\boldsymbol{\Upsilon}$, which provides fast calculations if a fast conversion algorithm is available for the $\boldsymbol{\Upsilon}$ and $\boldsymbol{\Psi}$ domain. For sparse signal information, we see a small set ofconversion coefficients $\mathbf{x}$ in $\boldsymbol{\Upsilon}$. Dimensions can be represented as $\mathbf{y} = \boldsymbol{\Phi}\mathbf{x}$ that $\boldsymbol{\Phi}$ matrix with $\mathrm{M} \times \mathrm{N}$ and $\mathrm{M} \ll \mathrm{N}$. Each row of $\boldsymbol{\Phi}$ is a subset of $\boldsymbol{\Upsilon}$ atoms. If $\boldsymbol{\Upsilon}$ and $\boldsymbol{\Psi}$ they are non-coherence and $\boldsymbol{\phi}_{\mathrm{i}}$ randomly selected, then they can$\mathbf{x}$ from $\mathbf{y}$ most likely be reconstructed.

2-1-3 sparse signal recovery

A definite solution for sparse signal recovery is to solve the norm-l_1 minimization problem:

$$\min\|\boldsymbol{\theta}\|_1 \text{ subject to } \boldsymbol{\Phi\Psi\theta} = \mathbf{y} \tag{10}$$

That $\|\boldsymbol{\theta}\|_1 = \sum_i|\boldsymbol{\theta}_i|$. The solution $\widehat{\boldsymbol{\theta}}$ to this problem is a sparse signal $\mathbf{x}^* = \boldsymbol{\Psi}\widehat{\boldsymbol{\theta}}$. The answer in Equation (10) provides a sparse representation of a signal that satisfies compact measurements. This method of reconstruction is called base chase (BP) (E. J. Candès et al., 2006) (Schwartz, 2011). Basic tracking is an efficient algorithm and can be accomplished with linear programming.
The following theorem, from (E. Candès & Tao, 2005) and RIP links the measurement matrix to the success of thin signal reconstruction.
Theorem: Berger et al., 2010) Suppose $\mathbf{x}$ is a signal with sparsity of S and also holds for isometric constants$\delta_{2s}$and δ_{3s} and relational$\delta_{2s} + \delta_{3s} < 1$, then the answer$\mathbf{x}^*$ corresponding to relation (10) is exact mean $\mathbf{x} = \mathbf{x}^*$. It is noteworthy that if fast algorithms are assigned to $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$, then the BP algorithm can be realized using fast algorithms that make it possible to recover a sparse signal with large dimensions. In practice, the resulting linear measurements are destroyed by noise and as

$$\mathbf{y}_n = \boldsymbol{\Phi\Psi\theta} + \mathbf{n} \tag{11}$$

Are modeled, which $\mathbf{n}$ is a Gaussian white noise with a mean of zero. The recovery algorithm must consider the effect of noise. The sparse signal can be classified according to the relation using $\mathbf{y}_n$ the Base Detection Algorithm (BPDN) as:

$$\min\|\boldsymbol{\Phi\Psi\theta} - \mathbf{y}_n\|_2^2 + \lambda\|\boldsymbol{\theta}\|_1 \text{ s,t, } \mathbf{y}_n = \boldsymbol{\Phi\Psi\theta} + \mathbf{n} \tag{12}$$

Obtained where $\lambda > 0$ depends on the noise level. Here λ balances the task of norm-l_2 minimization noise and norm-l_1 minimization sparse signal. Careful selection of the λ, has a significant effect on the estimated signal quality.
For stable sparse signal reconstruction, norm-l_1 minimization with noise measurements can be formulated with the LASSO problem. that's mean:

$$\min\|\boldsymbol{\theta}\|_1 \text{ s,t, } \|\boldsymbol{\Phi\Psi\theta} - \mathbf{y}\| \leq \varepsilon \tag{13}$$

Where ε limits noise power in size. Problem (13) is a convex problem and efficient algorithms can be developed to solve it. The following theorem shows how accurate this problem is.
Theorem: (E. Candès & Tao, 2005) Suppose $\delta_{2s} < \sqrt{2} - 1$ then to answer the problem (13):

$$\|\mathbf{x}^* - \mathbf{x}\|_2 \leq C_0\|\mathbf{x}^* - \mathbf{x}_s\|_1\sqrt{s} + C_1\varepsilon \tag{14}$$

Where C_0 and C_1 are positive constants and $\mathbf{x}_s$ an approximation of $\mathbf{x}$ which all its components except to the S largest of them are zero. This theorem shows that the reconstruction error is limited to two terms. The first expression is the approximation error and the second expression is the noise level. They are shown to be fixed and small (E. J. Candès et al., 2006). Therefore, stable reconstruction of the sparse signal is achieved even with noise sizes.

4. Challenges of M-MIMO Implementation and Work done in this Field

With the advent of 5G, new needs have emerged in wireless telecommunications systems, including improved spectral efficiency, energy efficiency, and more information security. One of the conclusions to be drawn from the previous discussion is that capacity increases linearly with increasing factor. This result shows that a system needs an appropriate number of antennas to meet the demand for spectral efficiency. This idea has led to extensive research under the name of M-MIMO that the number of transmitting and receiving antennas reaches 10 to 100 antennas (Mohammed et al., 2009). In these systems, the channel between each user and the BS will be asymptotically perpendicular to the other user's channel. Another important advantage of these systems is the efficient reduction of energy required for transmission, which makes this technology one of the most important technologies for next generation wireless communication systems.
In fact, M-MIMO systems are the same MIMO systems in which a large number of antennas of about 100 or more antennas are used in the base station. These types of MIMO systems have brought new features to telecommunication systems, especially multi-user systems. For example, in (Jacobsson et al., 2017), it has been shown that in a multi-user system, if the number of antennas used in BS is much greater than the number of users inside the cells, then by using

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simple processing techniques completely eliminate adverse effects such as noise and intracellular interference. Another advantage of M-MIMO systems is their ability to significantly reduce the power consumption of users as well as BS (Lu et al., 2014).
One of the most important and influential factors in the performance of M-MIMO systems is having channel information at the base station. This information is obtained by sending the pilot by the base station or users and estimating the channel. By using an array of antennas at the base station, the adverse effects of channel estimation can be reduced. The sparsity of the telecommunication channel in wireless systems means that very few channel coefficients are non-zero, providing the basis for the use of intensive measurement techniques and algorithms. Initial work focused on the issue of point-to-point links in MIMO, meaning that two devices with multiple antennas were connected to each other. In recent years, this issue has shifted to the more practical problem of multi-user systems. In this case, the BS serves multiple users simultaneously with multiple antennas, and the multiplexing benefit is shared among all users. In this method, expensive equipment is required only on the BS side and on the users side there can be only one or two simple antennas (Lu et al., 2014).
Another advantage of M-MIMO systems is the achievement of greater efficiency as well as simplification of signal processing. As mentioned, in these systems BS are equipped with more antennas in the order of about 100 or more. It has been shown that this feature, along with simple linear processing, has greatly improved energy efficiency and spectrum. When it comes to M-MIMO systems, we are looking for systems that, while having all the benefits of conventional MIMO systems, can serve a much larger number of users at a specific frequency and time.(Larsson et al., 2014). Challenges with M-MIMO generally include the lack of high-performance computational algorithms in signal recognition and channel estimation. The application of particle swarm optimization (PSO) for M-MIMO channel estimation has been proposed and investigated (Knievel & Hoeher, 2012). On the other hand, using several hundred antennas in a limited space, such as handheld systems, is very difficult.
Using M-MIMO, methods have been proposed for optimal use of dimensions and power (Rusek et al., 2013). The base station, which is usually not limited in energy and space, is equipped with several hundred antennas, while mobile stations are limited to one antenna. This method has several advantages, for example channel estimation for Faraso link can be simplified using series development methods. Due to the large number of antennas in the Ferroso link, beam formation is optimal.
One of the most important issues in M-MIMO is the pilot contamination due to the interference of the symbols. Generally, training sequences are orthogonally designed, although the number of orthogonal sequences is very small, in multicellular environments they must be split between adjacent cells, and the same pilot signals to estimate the channel to users. Which are located inside different cells. Pilot contamination, as shown in Figure (2), occurs when pilots are used in adjacent cells, and thus in the channel estimation phase, such as users' pilot signals. Adjacent cells are not perpendicular to each other, BS can not separate their channels from each other, and as a result, user channels located in different cells interfere with each other. Therefore, reducing the number of pilots required to estimate the thin channels made possible by the application of CS theory makes it possible to reduce pilot contamination in M-MIMO systems. An M-MIMO based system usually requires complex signal processing. Hence, much research has focused on the simplification and optimization of signal processing algorithms and their implementation. However, low-complexity algorithms generally reduce performance quality. This compromise is the most common scenario for any complex wireless system. For example, the more accurate the CSI, which increases performance, the greater the processing complexity. However, pilot contamination can be overcome using sophisticated channel estimation algorithms.

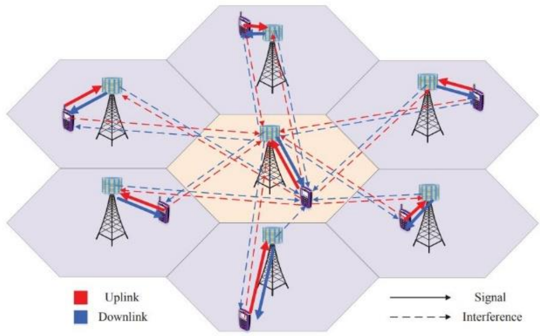

Figure2. Pilot contamination of adjacent cells in the Frasso and Froso links (Zheng et al., 2015).

The paper (Sadeghi and Azghani, 2021) proposes a sparse-based algorithm for more efficient channel estimation. For this purpose, a problem modeling is proposed to exploit the spatial correlation between different BS antennas as well as the similarity between the user of the channel support set. A repetition-based threshold method has been proposed to approximate the channel matrix, which has been effective in estimating the channel due to the large number of base station antennas and consequently the large number of channel paths.
The paper (Zhao et al, 2020) proposes a low complexity estimation algorithm based on compact measurement for multi-antenna mobile terminals to reduce the terminal computational overhead. In this design, the mobile terminal estimates the downlink

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massive multi-input multi-output channel and uses the spatial sparsity properties of the multi-input multi-output channel to reduce the overhead. Since the different antennas of a terminal have the same set of support, this algorithm estimates several indices in each iteration and collects the estimated indices of the different antennas at the end of each iteration. As a result, it reduces the total number of iterations of the algorithm. It then obtains a stop condition for a greedy algorithm that stops the iteration process due to the residual energy.

5- Simulation Results

Many works have expressed the channel estimation for the TDD scenario in order not to fall under the heavy load of the downlink pilot and its feedback, and have taken advantage of its reciprocity feature. As CSI in the downlink is obtained from the CSI uplink. The reciprocity nature of the channel cannot be implemented in FDD systems because in the FDD mode, the downlink and uplink use different frequency bands and the CSIs are proportional to the different uplink and downlinks. But this is not a reason to ignore these methods, because in many telecommunication systems, they are the dominant methods in data transfers. FDD works well in symmetric and delay-sensitive systems, and many cellular systems currently use FDD, so it can not be ignored. Usually, due to the low coherence time, it is not possible to consider the uplink channel specifications for downlink and this reduces the possibility of estimation accuracy in TDD. For this reason, in the simulation, we choose the FDD method and used the simulation specifications of the SOMP algorithm(Abedi et al, 2025). On the EPA channel at SNR = 20dB As shown in the figure(3), for β≥18/82%, the proposed algorithm and the proposed modified algorithm have similar MSE performance and their performance is similar to that of the LS algorithm. This indicates that the proposed algorithm can reliably obtain the sparse channel level and the backup set for β≥18/82%.

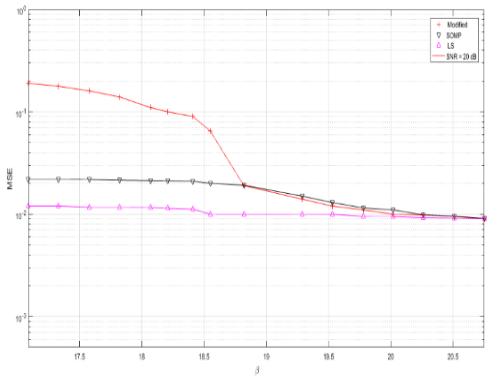

Figure3. Comparison of MSE performance of proposed algorithms and LS against pilot ratio and SNR = 20 dB.

6. Conclusion

In this paper, due to the importance of better specifying and estimating the channel of massive multi-input multi-output systems, we first examined the details of M-MIMO systems and with sparse signal and compact measurement and methods of sparse signal retrieval and its efficiency. We got acquainted with the fifth generation of wireless communications and then described their efficiency in the channel estimation systems used in the articles and examined their efficiency, and finally simulated our channel estimation algorithm using a compressive measurement to achieved fewer pilots and more efficient productivity.

References

[1] Baraniuk, R., Davenport, M., DeVore, R., & Wakin, M. (2008). A simple proof of the restricted isometry property for random matrices. Constructive Approximation, 28(3), 253–263. https://doi.org/10.1007/s00365-007-9003-x

[2] Baraniuk, R. G., Davenport, M. A., Duarte, M. F., & Hegde, C. (2011). An introduction to compressive sensing. http://cnx.org/content/col11133/latest

[3] Berger, C. R., Wang, Z., Huang, J., & Zhou, S. (2010). Application of compressive sensing to sparse channel estimation. IEEE Communications Magazine, 48(11), 164–174. https://doi.org/10.1109/MCOM.2010.5621984

[4] Boudreau, G., Panicker, J., Guo, N., Chang, R., Wang, N., & Vrzic, S. (2009). Interference coordination and cancellation for 4G networks. IEEE Communications Magazine, 47(4), 74–81. https://doi.org/10.1109/MCOM.2009.4907410

[5] Candès, E. J. (2006). Compressive sampling. International Congress of Mathematicians, ICM 2006, 3, 1433–1452. https://doi.org/10.4171/022-3/69

[6] Candes, E. J., & Romberg, J. K. (2005). Signal recovery from random projections. Computational Imaging III, 5674(626), 76. https://doi.org/10.1117/12.600722

[7] Candès, E. J., Romberg, J., & Tao, T. (2006). Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information. IEEE Transactions on Information Theory, 52(2), 489–509. https://doi.org/10.1109/TIT.2005.862083

[8] Candès, E., & Tao, T. (2005). Decoding by Linear ProgrammingEmmanuel Candes†. IEEE Trans. Inf. Theory, 51(12), 4203–4215.

[9] Jacobsson, S., Durisi, G., Coldrey, M., Goldstein, T., & Studer, C. (2017). Quantized Precoding for Massive MU-MIMO. IEEE Transactions on Communications, 65(11), 4670–4684. https://doi.org/10.1109/TCOMM.2017.2723000

[10] Johnson, W. B., & Naor, A. (2010). The Johnson-Lindenstrauss lemma almost characterizes Hilbert space, but not quite. Discrete and Computational Geometry, 43(3), 542–553. https://doi.org/10.1007/s00454-009-9193-z

[11] Keusgen, W. (2003). On limits of wireless communications when using multiple dual-polarized

antennas. 10th International Conference on Telecommunications, ICT 2003, 1, 204–210. https://doi.org/10.1109/ICTEL.2003.1191213

[12] Knievel, C., & Hoeher, P. A. (2012). On particle swarm optimization for MIMO channel estimation. Journal of Electrical and Computer Engineering, September. https://doi.org/10.1155/2012/614384

[13] Larsson, E. G., Edfors, O., Tufvesson, F., & Marzetta, T. L. (2014). Massive MIMO for next generation wireless systems. IEEE Communications Magazine, 52(2), 186–195. https://doi.org/10.1109/MCOM.2014.6736761

[14] Lu, L., Li, G. Y., Swindlehurst, A. L., Ashikhmin, A., & Zhang, R. (2014). An overview of massive MIMO: Benefits and challenges. IEEE Journal on Selected Topics in Signal Processing, 8(5), 742–758. https://doi.org/10.1109/JSTSP.2014.2317671

[15] Mietzner, J., Schober, R., Lampe, L., Gerstacker, W., & Hoeher, P. (2009). Multiple-antenna techniques for wireless communications - A comprehensive literature survey. IEEE Communications Surveys and Tutorials, 11(2), 87–105. https://doi.org/10.1109/SURV.2009.090207

[16] Mohammed, S. K., Zaki, A., Chockalingam, A., Member, S., Rajan, B. S., & Member, S. (2009). High-Rate Space – Time Coded Large-MIMO Systems : Low-Complexity Detection and Channel Estimation. 3(6), 958–974.

[17] Noor-A-Rahim, M., Saiful, M., Nashid, M., Kamal, M., & Z., A. (2011). Performance Analysis of MIMO-OFDM System Using Singular Value Decomposition and Water Filling Algorithm. International Journal of Advanced Computer Science and Applications, 2(4), 49–53. https://doi.org/10.14569/ijacsa.2011.020407

[18] Oestges, C., & Clerckx, B. (2007). MIMO Wireless Communications. MIMO Wireless Communications. https://doi.org/10.1016/B978-0-12-372535-6.X5000-4

[19] Rusek, F., Persson, D., Lau, B. K., Larsson, E. G., Marzetta, T. L., Edfors, O., & Tufvesson, F. (2013). Scaling up MIMO : Opportunities and challenges with very large arrays. IEEE Signal Processing Magazine, 30(1), 40–60. https://doi.org/10.1109/MSP.2011.2178495

[20] Sanguino, J., & Roberts, R. W. (2011). Wireless Communications Adapter For A Hearing Assistance Device. The Journal of the Acoustical Society of America, 129(4), 2354. https://doi.org/10.1121/1.3582201

[21] Schwartz, J. (2011). Pursuit of the gene; from Darwin to DNA. Isis; an International Review Devoted to the History of Science and Its Cultural Influences, 102(2), 129–159.

[22] Stüber, G. L., Barry, J. R., Mclaughlin, S. W., Li, Y. E., Ingram, M. A., & Pratt, T. G. (2004). Broadband MIMO-OFDM wireless communications. Proceedings of the IEEE, 92(2), 271–293. https://doi.org/10.1109/JPROC.2003.821912

[23] Zheng, K., Zhao, L., Mei, J., Shao, B., Xiang, W., & Hanzo, L. (2015). Survey of Large-Scale MIMO Systems. IEEE Communications Surveys and Tutorials, 17(3), 1738–1760. https://doi.org/10.1109/COMST.2015.2425294

[24] D. Zhao and T. Han, (2020) “Low-Complexity Compressed Sensing Downlink Channel Estimation for Multi-Antenna Terminals in FDD Massive MIMO Systems,” IEEE Access, vol. 8, pp. 130183–130193.

[25] N. Sadeghi and M. Azghani, (2021) “Channel Estimation using Block Sparse Joint Orthogonal Matching Pursuit in Massive MIMO Systems,” 26th Int. Comput. Conf. Comput. Soc. Iran, CSICC 2021.

[26] M.A. Abedi, A. Haghbin, F. Razazi, (2025) "Adaptive algorithm based on compressive sensing to improve the channel estimation of M-MIMO systems", Journal of Intelligent Procedures in Electrical Technology, vol. 16, no. 61, pp. 29-48, June 2025 (in Persian).